

Application of Machine Learning in Accounting Fraud Detection: A Systematic Literature Review

Ardian Bagus Septiawan¹, Saeful Bakhri², Gunawan Aji³

¹Universitas Islam Negeri K.H. Abdurrahman Wahid, Pekalongan, Indonesia

²Universitas Islam Negeri K.H. Abdurrahman Wahid, Pekalongan, Indonesia

³Universitas Islam Negeri K.H. Abdurrahman Wahid, Pekalongan, Indonesia

Corresponding Author: ardian.bagus.septiawan@mbs.uingsdur.ac.id

Submission: 24 December 2025

Revision: 26 December 2025

Accepted: 28 December 2025

Abstract

This study aims to examine the application of machine learning in detecting accounting fraud using a Systematic Literature Review (SLR) approach. The research seeks to understand how machine learning technology enhances audit effectiveness and improves the accuracy of identifying suspicious financial reports. The literature search was conducted through databases such as Google Scholar, Scopus, and IEEE Xplore, covering publications from 2015 to 2025. From an initial pool of 50 studies, 20 were screened for relevance, and 8 core articles were analyzed in depth. The results reveal that algorithms such as Random Forest, Support Vector Machine, and Neural Network achieve high accuracy in detecting financial anomalies. However, the success of implementation largely depends on data quality, model interpretation, and the readiness of human resources to adopt the technology ethically and responsibly.

Keywords: Accounting Fraud; Fraud Detection; Machine Learning; SLR

Abstrak

Penelitian ini bertujuan untuk mengkaji penerapan machine learning dalam mendeteksi kecurangan akuntansi melalui pendekatan Systematic Literature Review (SLR). Kajian ini dilakukan untuk memahami sejauh mana teknologi pembelajaran mesin mampu meningkatkan efektivitas audit dan akurasi dalam identifikasi laporan keuangan yang mencurigakan. Proses penelitian melibatkan penelusuran literatur dari berbagai basis data seperti Google Scholar, Scopus, dan IEEE Xplore dengan periode publikasi antara 2015 hingga 2025. Dari 50 artikel yang ditemukan, 20 artikel diseleksi lebih lanjut, dan 8 artikel utama dianalisis secara mendalam. Hasil penelitian menunjukkan bahwa algoritma seperti Random Forest, Support Vector Machine, dan Neural Network memiliki tingkat akurasi tinggi dalam mendeteksi anomali keuangan. Namun, keberhasilan implementasi sangat bergantung pada kualitas data, interpretasi hasil, dan kesiapan sumber daya manusia dalam mengadopsi teknologi secara etis dan bertanggung jawab.

Kata Kunci: Penipuan Akuntansi; Deteksi Penipuan; Pembelajaran Mesin; SLR

INTRODUCTION

Financial statement fraud refers to the deliberate falsification or manipulation of a company's financial information within its financial reports, with the intent to deceive or mislead investors, creditors, or other stakeholders. This practice encompasses a wide range of unethical business behaviors that deviate from accounting and ethical principles, such as inflating profit margins, overstating earnings, or providing misleading financial data about business operations. Financial statement fraud often involves fabricating reports, inflating stock prices, evading taxes, or securing bank loans through misrepresentation.¹ As technology advances, fraud detection methods must also evolve to effectively identify signs of fraud using digital tools. Fraud detection systems that operate through three main approaches—machine learning algorithms, data mining, and meta-learning—possess adaptive intelligence that improves continuously through iterative processes.²

A machine learning (ML) approach is particularly needed to ensure effective credit card fraud detection, as ML algorithms offer faster and more accurate fraud identification. However, challenges remain in selecting the most effective algorithm, continuously updating detection models, and balancing detection accuracy to minimize false positives.³ Nevertheless, applying ML to detect fraud in the financial sector is not without risks. Key factors include data quality, financial industry regulations, and technology adoption. Inconsistent data across financial datasets can degrade model performance, making it difficult to achieve high accuracy. Furthermore, model transparency remains a concern since some ML algorithms—particularly deep learning—produce opaque and hard-to-interpret results. Additionally, data privacy and security are critical issues in such applications due to the sensitive nature of financial information.

The role of security in technology, policy, and education is to ensure the confidentiality, integrity, and availability of data during storage, processing, and transmission. Generally, security systems operate through three key functions: prevention, detection, and correction. In the field of artificial intelligence, data security can be enhanced using machine learning techniques, which are highly adaptable to changing environments, making them well-suited for proactive prevention, accurate detection, and effective mitigation of security threats.⁴

Studies on the application of machine learning in accounting fraud detection have shown growing interest in automating audit processes and identifying financial anomalies. Mia et al. (2025) highlighted the effectiveness of *Gradient Boosting Machines* in detecting fraudulent financial

1 Sindu Prasetyo and Totok Dewayanto, "Penerapan Machine Learning, Deep Learning, Dan Data Mining Dalam Deteksi Kecurangan Laporan Keuangan-a Systematic Literature Review," *Diponegoro Journal of Accounting* 13, no. 3 (2024): 1–12.

2 Dian Kristiyani and Hamidah, "Model Penerapan Akuntansi Sektor Publik untuk Mencegah Fraud pada Sektor Publik di Era Digital," *Jurnal Bisnis Dan Akuntansi*, 2020.

3 M S U Hayati and P B Hadiprajitno, "Penerapan Machine Learning dan Deep Learning pada Peningkatan Deteksi Credit Card Fraud - A Systematic Literature Review," *Diponegoro Journal of ...* 1203011612, no. 2022 (2021): 19840503.

4 Nuruddin Wiranda, Fal Sadikin, and Wanvy Arifha Saputra, "Pembelajaran Mesin Untuk Sistem Keamanan - Literatur Review," *IJEIS (Indonesian Journal of Electronics and Instrumentation Systems)* 12, no. 1 (2022): 37, <https://doi.org/10.22146/ijeis.69022>.

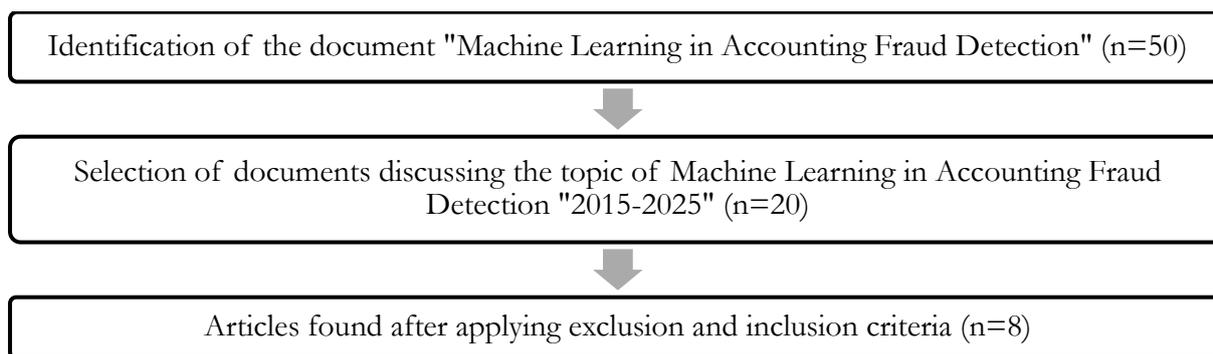
statements but did not address the interpretability of models for human auditors.⁵ Araújo (2025) emphasized the balance between algorithmic efficiency and ethical use of AI but did not examine its impact on real-world audit governance.⁶ Jeon et al. (2025) applied machine learning to analyze medical risk factors but did not adapt this longitudinal approach to accounting contexts.⁷ Kavoni et al. (2025) explored process optimization using ML but did not connect it to financial statement manipulation prediction.⁸ Maharajpet and Hegde (2025) focused on real-time detection but have not applied it to automated financial monitoring systems.⁹

Based on these research gaps, this study aims to conduct a systematic review of machine learning applications in accounting fraud detection, examining the models, methods, and algorithmic effectiveness reported across existing studies. The research seeks to identify the most accurate and efficient algorithms—such as *Random Forest*, *Support Vector Machine*, and *Gradient Boosting*—for detecting financial statement manipulation. Furthermore, it aims to evaluate how interpretability, transparency, and ethical considerations are integrated into audit and financial governance contexts. The findings are expected to provide a comprehensive understanding of current advancements, methodological limitations, and innovation pathways to strengthen intelligent fraud detection systems.

Method

This study employs a Systematic Literature Review (SLR) approach to examine the application of *machine learning* in detecting accounting fraud. This method was chosen because it provides a structured and objective way to identify, evaluate, and synthesize previous research findings.¹⁰ The review process follows the guidelines proposed by Kitchenham, consisting of three main stages: planning, execution, and reporting. The review focuses on literature discussing the use of *machine learning* algorithms in auditing, financial reporting, and fraud prevention. Through this approach, the study aims to present a comprehensive understanding of research trends and the practical relevance of machine learning technologies within the modern accounting field.

-
- 5 Mohammad Musa Mia et al., “Enhancing Financial Statement Fraud Detection through Machine Learning: A Comparative Study of Classification Models,” *The American Journal of Engineering and Technology* 07, no. 09 (September 17, 2025): 166–75, <https://doi.org/10.37547/tajet/Volume07Issue09-11>.
 - 6 Daniela Cristina Abreu Jové de Araújo, “Artificial Intelligence and Machine Learning in Fraud Detection: Practical Applications, Predictive Models, and Ethical Risks,” *Revista Ft* 29, no. 150 (September 7, 2025): 22–23, <https://doi.org/10.69849/revistaft/ra10202509071822>.
 - 7 Jae Hyung Jeon, Jaewoo Chung, and Nam-Kyu Lim, “A Longitudinal Investigation of Stage 2 Pressure Injury Outcomes With Machine Learning Technique to Identify Relevant Factors,” *Advances in Skin & Wound Care* 38, no. 9 (October 2025): E81–89, <https://doi.org/10.1097/ASW.0000000000000347>.
 - 8 Hossein Kavoni et al., “Machine Learning-Driven Optimization of Culture Conditions and Media Components to Mitigate Charge Heterogeneity in Monoclonal Antibody Production: Current Advances and Future Perspectives,” *MAbs* 17, no. 1 (December 31, 2025), <https://doi.org/10.1080/19420862.2025.2547084>.
 - 9 Sheela S Maharajpet and Ananya V Hegde, “Intelligent Real-Time Crowd Density Estimation for Proactive Event Safety: A Machine Learning Approach,” *Recent Research Reviews Journal* 4, no. 2 (December 2025): 264–80, <https://doi.org/10.36548/rrrj.2025.2.005>.
 - 10 Neal R. Haddaway et al., “PRISMA2020 : An R Package and Shiny App for Producing PRISMA 2020-compliant Flow Diagrams, with Interactivity for Optimised Digital Transparency and Open Synthesis,” *Campbell Systematic Reviews* 18, no. 2 (June 27, 2022), <https://doi.org/10.1002/cl2.1230>.

Table 1. Article Selection Scheme

Source: from Author

The literature search was conducted using several academic databases, including Google Scholar, Scopus, and IEEE Xplore, with keywords such as “*Machine Learning in Accounting Fraud Detection*”, “*Financial Fraud Prevention*”, and “*Artificial Intelligence in Audit*”. The inclusion criteria covered English and Indonesian peer-reviewed journal articles published between 2015 and 2025. The initial search identified 50 relevant studies. After applying screening criteria based on thematic relevance and methodological completeness, 20 studies were selected for further review. From these, 8 core articles were retained for in-depth analysis due to their significant contribution and robust methodological design, representing the most relevant evidence base for this research.

The analysis process involved categorizing each article based on the type of algorithm used, its application context, and the key findings reported. Narrative synthesis was then conducted to identify patterns, advantages, and limitations in the use of *machine learning* for accounting fraud detection. The findings were further organized according to algorithmic approaches—such as *Random Forest*, *Support Vector Machine*, and *Deep Learning*—to highlight performance trends across financial sectors. Beyond technical aspects, the analysis also considered ethical and social dimensions, focusing on how ML adoption influences transparency, accountability, and public trust in the accounting profession within the digital era.

RESULTS AND DISCUSSION

Application of Machine Learning in Detecting Accounting Fraud

The rapid development of artificial intelligence has brought a major transformation to modern accounting practices, particularly in detecting and preventing financial fraud. *Machine learning* (ML) has emerged as one of the most promising approaches due to its ability to automatically recognize anomalous patterns within large datasets. In the context of auditing and financial reporting, ML is not only used to detect irregular transactions but also to enhance data-driven decision-making processes. The implementation of this technology marks a paradigm shift from traditional manual detection toward an intelligent and adaptive system capable of handling the complexity of financial data.

This study maps various research examining the application of ML in detecting accounting fraud. Based on a *Systematic Literature Review* of eight relevant studies, a general overview was obtained regarding the types of algorithms used, their application areas, and their effectiveness within audit and financial reporting contexts. The following table summarizes the key findings from each study, including the author’s name, research focus, and major results related to ML

performance in fraud detection. This mapping provides a comprehensive understanding of current trends and directions in ML-based fraud detection research over the past decade.

Table 2. Summary of Studies on the Application of Machine Learning

Author	Research Focus	Key Findings
Judijanto et al. (2024)	AI and ML in financial auditing	ML accelerates auditing and identifies irregular transaction patterns
Shinta Dewi & Dewayanto (2024)	Big Data and ML in financial fraud	AutoML and real-time analytics improve detection efficiency
Suarsa et al. (2021)	Audit risk using ML	ML helps auditors recognize fraud risks more quickly
Permana et al. (2024)	ML for financial fraud detection	RF and GBM are effective for imbalanced datasets
Hayati & Hadiprajitno (2021)	ML & DL in credit card fraud	Hybrid models and SMOTE improve detection accuracy
Prasetyo & Dewayanto (2024)	ML, DL, and data mining in financial reports	Algorithm combinations enhance audit reliability
Zalukhu et al. (2023)	ML in startups	SmartPLS shows strong adoption potential for ML
Utomo & Djaddang (2025)	Fraud Pentagon and ML	Competence and rationalization significantly influence fraud behavior

Source: from Author

From the table above, it is evident that research on the application of *machine learning* in detecting accounting fraud has grown significantly in recent years. Nearly all studies demonstrate that ML helps auditors and financial managers recognize unusual transactions faster and more accurately than traditional approaches. For instance, algorithms such as *Decision Tree* and *Random Forest* are used to classify potentially fraudulent transactions, while *Support Vector Machine (SVM)* performs well on high-dimensional financial data with many variables.

The study by Judijanto et al. emphasizes that integrating AI and ML technologies in auditing represents a revolution in conventional accounting practices.¹¹ Through large-scale data analysis, auditors can identify anomalous patterns that were previously difficult to detect manually. This study highlights ML not merely as a tool but as an analytical partner capable of accelerating evidence-based decision-making. Similarly, Shinta Dewi & Dewayanto underline the effectiveness of *AutoML* in producing efficient and adaptive fraud detection models that respond dynamically to real-time financial data changes.¹²

Another study by Suarsa et al. highlights ML's role in reducing audit risk. By leveraging historical data, ML models can predict potential fraud occurrences in companies with a high level of accuracy.¹³ This helps auditors prioritize high-risk areas before conducting manual reviews.

11 Loso Judijanto et al., "Implementasi Teknologi Artificial Intelligence Dan Machine Learning Dalam Praktik Akuntansi Dan Audit: Sebuah Revolusi Atau Evolusi?" 1, no. 6 (2024): 470–83.

12 Finecia Shinta Dewi and Totok Dewayanto, "Peran Big Data Analytics, Machine Learning, Dan Artificial Intelligence Dalam Pendeteksian Financial Fraud: A Systematic Literature Review," *Diponegoro Journal of Accounting* 13, no. 3 (2024): 1–15.

13 Abin Suarsa, Eka Mulyani, and Verawaty, "Audit Risk: Machine Learning Untuk Klasifikasi Kecurangan Pada Perusahaan," *Sustainability Accounting & Finance Journal* 1, no. 2 (2021): 1–8.

Meanwhile, Permana et al. stress the advantages of *Random Forest (RF)* and *Gradient Boosting Machines (GBM)* in addressing data imbalance problems within fraud detection datasets.¹⁴ These algorithms deliver stable and consistent classification outcomes, even when fraudulent data are limited.

Hayati & Hadiprajitno broaden the scope by combining *machine learning* and *deep learning* to detect credit card fraud.¹⁵ Their approach applies *SMOTE* and *GAN* techniques to balance the disproportionate data between legitimate and fraudulent transactions. The results show significant improvement in both accuracy and sensitivity. Similarly, Prasetyo & Dewayanto (2024) found that combining several algorithms—such as *logistic regression*, *XGBoost*, and *Decision Tree*—strengthens fraud detection reliability and enhances transparency in digital audit processes.¹⁶

Meanwhile, Zalukhu et al. explore ML application within startup environments. Using *SmartPLS* to validate adoption models, their study reveals that ML holds strong potential to drive digital business efficiency.¹⁷ Utomo & Djaddang integrate the *Fraud Pentagon* model with ML and find that rationalization and competence are key behavioral factors contributing to accounting fraud.¹⁸ Thus, the implementation of ML is not only technological but also reinforces the psychological and behavioral dimensions of fraud prevention.

Overall, the mapping results demonstrate that *machine learning* has made a substantial impact on detecting accounting fraud across various sectors. Algorithms such as *Random Forest*, *Neural Network*, and *Support Vector Machine* have proven effective in enhancing audit efficiency, classification accuracy, and detection speed. However, the success of implementation heavily depends on data quality and the users' ability to interpret model outcomes. ML application should also be accompanied by strong ethical and regulatory awareness to prevent misinterpretation or bias during financial supervision.

Analysis of the Effectiveness and Challenges of Implementing Machine Learning

The development of *machine learning* (ML) has introduced a new paradigm in the field of accounting, particularly in auditing and financial reporting.¹⁹ This technology enables accountants to identify irregular transaction patterns with a level of precision and speed that traditional manual reviews cannot achieve. By analyzing large and complex datasets, ML strengthens internal control systems and enhances the transparency of financial statements. From a social perspective, its

14 Raka Permana et al., "Analisis Penggunaan Machine Learning Untuk Deteksi Penipuan Di Sektor Keuangan : Tinjauan Literatur" 2, no. 2 (2024): 244–48.

15 Hayati and Hadiprajitno, "Penerapan Machine Learning dan Deep Learning pada Peningkatan Deteksi Credit Card Fraud - A Systematic Literature Review."

16 Prasetyo and Dewayanto, "Penerapan Machine Learning, Deep Learning, Dan Data Mining Dalam Deteksi Kecurangan Laporan Keuangan-a Systematic Literature Review."

17 Hospitalia Zalukhu et al., "Penggunaan Machine Learning Dalam Startup Dengan Pemanfaatan Smart Pls," *Jurnal MENTARI: Manajemen, Pendidikan Dan Teknologi Informasi* 2, no. 2 (2023): 111–22, <https://doi.org/10.33050/mentari.v2i2.424>.

18 Widarto Rachbini Muhamad Rifais Utomo, Syahril Djaddang, "Deteksi Kecurangan Akuntansi Dengan Pendekatan Fraud Pentagon (Studi Pada Perusahaan Sektor Perbankan Yang Terdaftar Di BEI Periode 2013 – 2019) Muhamad" 4 (2025): 61–80.

19 Mohamed Ali Bejjar and Yosr Siala, "Machine Learning," in *Artificial Intelligence Approaches to Sustainable Accounting*, 2024, 110–34, <https://doi.org/10.4018/979-8-3693-0847-9.ch007>.

adoption has the potential to increase public trust in financial institutions, as data-driven auditing is viewed as more objective and evidence-based.

In terms of effectiveness, the application of ML in accounting has shown significant promise. Algorithms such as *Random Forest*, *Support Vector Machine*, and *Gradient Boosting* can detect anomalies that may indicate potential fraud.²⁰ These models reduce human error and shorten the time required for audits. However, their accuracy depends heavily on the quality of the financial data used. Incomplete or unclean data may lead to misclassification of legitimate transactions. As demonstrated by Prasetyo and Dewayanto, models trained on unstructured data tend to produce false positives, which could create misunderstanding or even misjudgment in audit conclusions.

Another major challenge lies in the interpretability of ML models. Algorithms like *deep learning* are often referred to as “black boxes” because their internal decision-making processes are difficult to explain.²¹ In auditing, this lack of transparency can be problematic since auditors must understand and justify the reasoning behind every finding. Judijanto and colleagues highlight that limited model interpretability can undermine the credibility of audit results, especially when algorithmic outputs are accepted without human verification. This underscores the importance of maintaining balance between technological capability and professional judgment in accounting practice.

Human resource readiness also plays a crucial role in the successful implementation of ML. Many accounting professionals still rely on conventional analytical skills and are less familiar with data-driven methodologies. Yet, understanding algorithmic logic and statistical interpretation is essential to use ML effectively. Zalukhu and colleagues emphasize that data literacy and specialized training for accountants are necessary so that they can interpret model outputs responsibly and avoid overreliance on automated systems. This transformation requires integrating data analytics into accounting education and professional development.

From an ethical and regulatory standpoint, implementing ML introduces new responsibilities for the accounting profession. Handling sensitive financial data demands strict compliance with privacy and data protection standards. Utomo and Djaddang point out that ethical considerations and individual rationalization play a critical role in the occurrence of fraud. Therefore, the adoption of ML should be accompanied by a renewed ethical framework that defines acceptable boundaries for algorithmic decision-making, ensuring transparency and fairness in automated audits. Upholding these standards is vital to preserving public confidence in financial reporting amid rapid digitalization.

Socioeconomic disparities also influence how ML is adopted in practice. Large firms with advanced technological infrastructure can implement ML more easily than smaller organizations with limited resources. Suarsa and colleagues explain that this technological divide can lead to unequal levels of transparency and audit quality across institutions. To ensure fairness, public policy and professional bodies must provide support—through incentives, technical guidance, and

20 Francis Effirim Botchey, Zhen Qin, and Kwesi Hughes-Lartey, “Mobile Money Fraud Prediction—A Cross-Case Analysis on the Efficiency of Support Vector Machines, Gradient Boosted Decision Trees, and Naïve Bayes Algorithms,” *Information* 11, no. 8 (July 31, 2020): 383, <https://doi.org/10.3390/info11080383>.

21 Vikas Hassija et al., “Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence,” *Cognitive Computation* 16, no. 1 (January 24, 2024): 45–74, <https://doi.org/10.1007/s12559-023-10179-8>.

infrastructure—to make ML adoption more inclusive across the accounting sector.²² From a societal viewpoint, the use of ML in auditing goes beyond efficiency; it shapes public perception of financial integrity. When audit processes are transparent and data-driven, public trust in institutions increases. Conversely, unaccountable or poorly implemented systems may erode that trust. Thus, the role of accountants extends beyond being technology users—they serve as ethical stewards who ensure that technological advances align with professional integrity and public interest.

Overall, *machine learning* represents a powerful tool in detecting accounting fraud, but its effectiveness depends on the harmony between technology, human expertise, and governance. Its adoption should be seen not merely as a technical innovation but as part of a broader effort to strengthen ethical and transparent financial management. As noted by Shinta Dewi and Dewayanto, the true success of ML lies not in how advanced its algorithms are, but in how well it upholds honesty, fairness, and accountability in accounting practices—values that ultimately serve both the profession and society.

CONCLUSION

The findings of this study indicate that machine learning (ML) plays a significant role in improving the efficiency, accuracy, and objectivity of accounting fraud detection. Various algorithms, such as Random Forest, Support Vector Machine, Neural Network, and Gradient Boosting, demonstrated strong performance in identifying anomalous financial transactions that may indicate fraudulent behavior. The integration of ML into auditing allows faster data analysis and enhances transparency in financial reporting. However, its effectiveness is largely dependent on the quality of data, model interpretability, and the auditor's ability to contextualize the results within accounting principles and ethical considerations.

This research contributes to the accounting field by providing a systematic overview of how ML has been applied to detect fraud and strengthen governance mechanisms. It highlights the growing intersection between accounting, data science, and ethics, offering a framework for integrating advanced analytics into professional audit practice. The study also emphasizes the importance of human oversight in maintaining fairness and accountability, showing that technology should complement rather than replace professional judgment. For practitioners, the findings serve as a reference to enhance audit strategies, while for academics, they provide a foundation for further exploration into AI-driven auditing systems.

Despite its valuable insights, this research has several limitations. The review relies on secondary data and focuses mainly on published studies between 2015 and 2025, which may not capture the latest emerging models or real-time applications. Additionally, variations in data quality and methodology across the reviewed studies limit direct comparability of results. Future research should focus on developing interpretable ML models that balance accuracy and transparency, as well as on conducting empirical studies in diverse accounting environments. Strengthening collaboration between accountants, data scientists, and policymakers will also be crucial to ensure that ML contributes ethically and sustainably to the advancement of financial integrity.

22 Raluca Ionescu, "Adopting Cloud Computing and Big Data Analytics to Enhance Public Sector Transparency and Accountability Through Artificial Intelligence," *Nuvern Machine Learning Reviews* 2, no. 1 (2025): 1–18, <https://nuvern.com/index.php/nmlr/article/view/4>.

BIBLIOGRAPHY

- Araújo, Daniela Cristina Abreu Jové de. “Artificial Intelligence and Machine Learning in Fraud Detection: Practical Applications, Predictive Models, and Ethical Risks.” *Revista Ft* 29, no. 150 (September 7, 2025): 22–23. <https://doi.org/10.69849/revistaft/ra10202509071822>.
- Bejjar, Mohamed Ali, and Yosr Siala. “Machine Learning.” In *Artificial Intelligence Approaches to Sustainable Accounting*, 110–34, 2024. <https://doi.org/10.4018/979-8-3693-0847-9.ch007>.
- Botchey, Francis Effrim, Zhen Qin, and Kwesi Hughes-Lartey. “Mobile Money Fraud Prediction—A Cross-Case Analysis on the Efficiency of Support Vector Machines, Gradient Boosted Decision Trees, and Naïve Bayes Algorithms.” *Information* 11, no. 8 (July 31, 2020): 383. <https://doi.org/10.3390/info11080383>.
- Dian Kristiyani, and Hamidah. “Model Penerapan Akuntansi Sektor Publik untuk Mencegah Fraud pada Sektor Publik di Era Digital.” *Jurnal Bisnis Dan Akuntansi*, 2020.
- Haddaway, Neal R., Matthew J. Page, Chris C. Pritchard, and Luke A. McGuinness. “PRISMA2020 : An R Package and Shiny App for Producing PRISMA 2020-compliant Flow Diagrams, with Interactivity for Optimised Digital Transparency and Open Synthesis.” *Campbell Systematic Reviews* 18, no. 2 (June 27, 2022). <https://doi.org/10.1002/cl2.1230>.
- Hassija, Vikas, Vinay Chamola, Atmesh Mahapatra, Abhinandan Singal, Divyansh Goel, Kaizhu Huang, Simone Scardapane, Indro Spinelli, Mufti Mahmud, and Amir Hussain. “Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence.” *Cognitive Computation* 16, no. 1 (January 24, 2024): 45–74. <https://doi.org/10.1007/s12559-023-10179-8>.
- Hayati, M S U, and P B Hadiprajitno. “Penerapan Machine Learning dan Deep Learning pada Peningkatan Deteksi Credit Card Fraud - A Systematic Literature Review.” *Diponegoro Journal of ...* 1203011612, no. 2022 (2021): 19840503.
- Ionescu, Raluca. “Adopting Cloud Computing and Big Data Analytics to Enhance Public Sector Transparency and Accountability Through Artificial Intelligence.” *Nuvern Machine Learning Reviews* 2, no. 1 (2025): 1–18. <https://nuvern.com/index.php/nmlr/article/view/4>.
- Jeon, Jae Hyung, Jaewoo Chung, and Nam-Kyu Lim. “A Longitudinal Investigation of Stage 2 Pressure Injury Outcomes With Machine Learning Technique to Identify Relevant Factors.” *Advances in Skin & Wound Care* 38, no. 9 (October 2025): E81–89. <https://doi.org/10.1097/ASW.0000000000000347>.
- Judijanto, Loso, Al Amin, Lukman Nurhakim, Universitas Airlangga, Al Amin, and Lukman Nurhakim. “Implementasi Teknologi Artificial Intelligence Dan Machine Learning Dalam Praktik Akuntansi Dan Audit: Sebuah Revolusi Atau Evolusi?” 1, no. 6 (2024): 470–83.
- Kavoni, Hossein, Iman Shahidi Pour Savizi, Saratram Gopalakrishnan, Nathan E. Lewis, and Seyed Abbas Shojaosadati. “Machine Learning-Driven Optimization of Culture Conditions and Media Components to Mitigate Charge Heterogeneity in Monoclonal Antibody Production: Current Advances and Future Perspectives.” *MAbs* 17, no. 1 (December 31, 2025). <https://doi.org/10.1080/19420862.2025.2547084>.
- Maharajpet, Sheela S, and Ananya V Hegde. “Intelligent Real-Time Crowd Density Estimation for Proactive Event Safety: A Machine Learning Approach.” *Recent Research Reviews Journal* 4, no. 2 (December 2025): 264–80. <https://doi.org/10.36548/rrrj.2025.2.005>.

- Mia, Mohammad Musa, Abdullah Al Mamun, Md Parvez Ahmed, Sanjida Akter Tisha, S M Ahsan Habib, and Fariha Noor Nitu. "Enhancing Financial Statement Fraud Detection through Machine Learning: A Comparative Study of Classification Models." *The American Journal of Engineering and Technology* 07, no. 09 (September 17, 2025): 166–75. <https://doi.org/10.37547/tajet/Volume07Issue09-11>.
- Muhamad Rifais Utomo, Syahril Djaddang, Widarto Rachbini. "Deteksi Kecurangan Akuntansi dengan Pendekatan Fraud Pentagon (Studi Pada Perusahaan Sektor Perbankan Yang Terdaftar Di BEI Periode 2013 – 2019) Muhamad" 4 (2025): 61–80.
- Permana, Raka, Ibrohim Syakur, Arif Rizqi Nugroho, and Bagas Adi Kurniawan. "Analisis Penggunaan Machine Learning Untuk Deteksi Penipuan Di Sektor Keuangan : Tinjauan Literatur" 2, no. 2 (2024): 244–48.
- Prasetyo, Sindu, and Totok Dewayanto. "Penerapan Machine Learning, Deep Learning, Dan Data Mining Dalam Deteksi Kecurangan Laporan Keuangan-a Systematic Literature Review." *Diponegoro Journal of Accounting* 13, no. 3 (2024): 1–12.
- Shinta Dewi, Finecia, and Totok Dewayanto. "Peran Big Data Analytics, Machine Learning, Dan Artificial Intelligence Dalam Pendeteksian Financial Fraud: A Systematic Literature Review." *Diponegoro Journal of Accounting* 13, no. 3 (2024): 1–15.
- Suarsa, Abin, Eka Mulyani, and Verawaty. "Audit Risk: Machine Learning Untuk Klasifikasi Kecurangan Pada Perusahaan." *Sustainability Accounting & Finance Journal* 1, no. 2 (2021): 1–8.
- Wiranda, Nuruddin, Fal Sadikin, and Wanvy Arifha Saputra. "Pembelajaran Mesin Untuk Sistem Keamanan - Literatur Review." *IJEIS (Indonesian Journal of Electronics and Instrumentation Systems)* 12, no. 1 (2022): 37. <https://doi.org/10.22146/ijeis.69022>.
- Zalukhu, Hospitalia, Kristinus Wibowo Dwi Prastiyanto, Adinur subarkah, Indra Ramadhan, and Nabilla Rizky Ramadhan. "Penggunaan Machine Learning Dalam Startup Dengan Pemanfaatan Smart Pls." *Jurnal MENTARI: Manajemen, Pendidikan Dan Teknologi Informasi* 2, no. 2 (2023): 111–22. <https://doi.org/10.33050/mentari.v2i2.424>.